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ORIGINAL ARTICLE

Rolling force prediction in cold rolling process based on combined method of T-S fuzzy neural network and analytical model

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Abstract
In the cold rolling process, inaccurate rolling force settings and the resulting strip thickness fluctuations and other quality problems occur, reducing the yield and product quality. To improve the accuracy of rolling force prediction, this paper proposes three methods to combine a T-S fuzzy neural network and rolling force analytical model based on their advantages and characteristics, to construct a combined rolling force prediction model, and to fully utilize the features and benefits of each model for rolling force prediction. The model's performance is evaluated by selecting the mean absolute error (MAE), mean absolute percentage error (MAPE), and root mean squared error (RMSE). The model experiments with historical production data obtained from industrial sites. The experimental results show that the combined prediction models have a more robust rolling force prediction capability than the T-S fuzzy neural network model alone, especially the combined form of using the calculated value of the rolling force analytical model as the input to the T-S fuzzy neural network without destroying the self-learning of the rolling force analytical model, which has better calculation accuracy and reliability for rolling force than other models. The model can provide an essential reference for the online prediction of cold rolling force and high precision rolling production and has high usability.

Keywords Cold rolling process · Rolling force prediction · T-S fuzzy neural network · Rolling force analytical model

1 Introduction

The market need for cold-rolled strip steel has increased dramatically due to the rapid growth of society. To maintain international competitiveness, steel enterprises have also put forward higher requirements for the quality of strip steel products, such as external dimensional accuracy, surface quality, and thickness accuracy [1]. In production, the mathematical model of cold rolling of strip steel is a mathematical expression describing the intrinsic laws of the cold rolling process. It is the soul of automatic industrial computer control. The calculation accuracy of the model can primarily affect the yield, quality, cost, and efficiency of the rolled product. To optimize the rolling production process and improve the performance of the rolling mill system, control plays a decisive role. As the core of the mathematical model for cold rolling, the rolling force model is the foundation for thickness control and plate shape calculation. It is an essential indicator in determining product accuracy. Therefore, the accuracy of the rolling force setting is vital in controlling the strip product quality. However, steel strip production is a sophisticated process consisting of smelting, continuous casting, hot rolling, and cold rolling processes. There is a strong genetic evolutionary relationship between the processes.

The traditional rolling force analytical model relies on the single cold rolling process, ignoring the genetic influence of key hot rolling process parameters, such as finish rolling

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temperature, coiling temperature, and other factors on the cold rolling force, as well as the inability to consider the nonlinear, highly coupled, and other complex influencing factors in the cold and hot rolling process. This reduces the precision of analytical models set up based on the rolling mechanism, which ultimately affects the control accuracy of quality indicators such as cold-rolled strip thickness and flatness. With the rapid rise of artificial intelligence technology, the use of intelligent algorithms to solve the problems of product quality stability and production efficiency due to the complexity of working conditions is gradually becoming the future development direction of strip rolling. Zhou et al. [2] used a neural network model to correct the deformation resistance and friction coefficient to improve the model's cold rolling force calculation accuracy. Liu et al. [3] predicted the rolling force in five stands by selecting the measured data of cold rolling sets as the input to a fuzzy cerebellar model neural network. Zhang et al. [4] constructed a rolling force model based on a genetic algorithm optimized BP neural network by selecting actual measured parameters of cold rolling as input. Guo et al. [5] concluded that the main factors affecting the accuracy of rolling force prediction were the deformation resistance of the material and the friction factor, so the two were modified by the parameter adaptive method, which eventually improved the prediction accuracy of the cold rolling force. Lin [6] simulated the rolling process using the finite element approach, and the data obtained from the simulation were used in the neural network for rolling force prediction.

Although the above studies considered the use of artificial intelligence algorithms in the rolling force modeling process, they are still limited to the single process of cold rolling without considering the genetic influence of the parameters of the hot rolling production process on the cold rolling process. There is the problem of isolation between the hot and cold rolling processes. Although the intelligent algorithm model can achieve a large amount of fast information operation, its "hollow" model structure does not reflect the physical meaning of the parameters and processes and cannot effectively explain the rolling process. Given the rigorous theoretical system and physical significance of the rolling force analytical model itself, this paper considers combining the analytical model with the data-driven model, making full use of the characteristics and advantages of various models, supported by a large amount of field data. Then, the knowledge of data statistics is used to summarize the laws needed for the model and make error corrections to the purely theoretical model to improve the rolling force model prediction accuracy.

This paper proposes three ways to combine the T-S fuzzy neural network model and the rolling force analytical model based on their advantages and characteristics to construct a combined model predicting rolling force and fully utilize each model's features and benefits for each model rolling force prediction. Figure 1 shows the operational structure of the combined model. Based on the hot and cold rolling process parameters that impact the rolling force, the rolling force's prediction and rolling parameters' preset for each stand can be achieved through a rolling force prediction combined model. A comparison of the experimental results shows that without destroying the self-learning of the rolling force analytical model when its calculated value is directly used as an input terminal of the T-S fuzzy neural network, it dramatically improves the accuracy of the roll force prediction and has a more robust roll force prediction capability compared with other forms of combined models. This is suitable for online application in multiroll cold rolling mills and can satisfy the requirements of high precision production in industrial sites.

2 T-S fuzzy neural network

2.1 T-S fuzzy control system

In 1965, American professor Zadeh first introduced the concept of fuzzy mathematics and fuzzy control and later proposed fuzzy algorithms, which have become widely used in robotics, process control, fault diagnosis, and image processing. The main feature of the fuzzy control is a computer mathematical model that simulates linguistic variables to describe fuzzy concepts in the control of complex objects and empirical-based control rules to describe the fuzzy relationships (models) between the objects' input–output turn enable fuzzy logic reasoning. Fuzzy control avoids the complex mathematical models required in traditional control processes and is an effective control path for nonlinear modeling systems [7]. The most critical component of a fuzzy control system is the fuzzy controller, and the performance of which depends on whether the whole control system can better achieve its control capability. Figure 2 shows the components of a fuzzy controller. The fuzzification module, knowledge base module, fuzzy inference machine module, and anti-fuzzification module are included.

The input variables are exact quantities in a fuzzy control system, but the actual values must be converted into discrete portions during logical reasoning, i.e., fuzzy linguistic variables. Therefore, the role of the fuzzification module is to convert the exact value of the input variable into a fuzzy linguistic variable described by the degree of affiliation after preprocessing, the knowledge-based module determines the performance of the fuzzy controller and is the core of the fuzzy controller, and the fuzzy reasoner module simulates human decision reasoning ability and converts the fuzzy "If–Then" rule from a fuzzy rule base into a mapping according to fuzzy logic rules. The fuzzy controller obtains a fuzzy

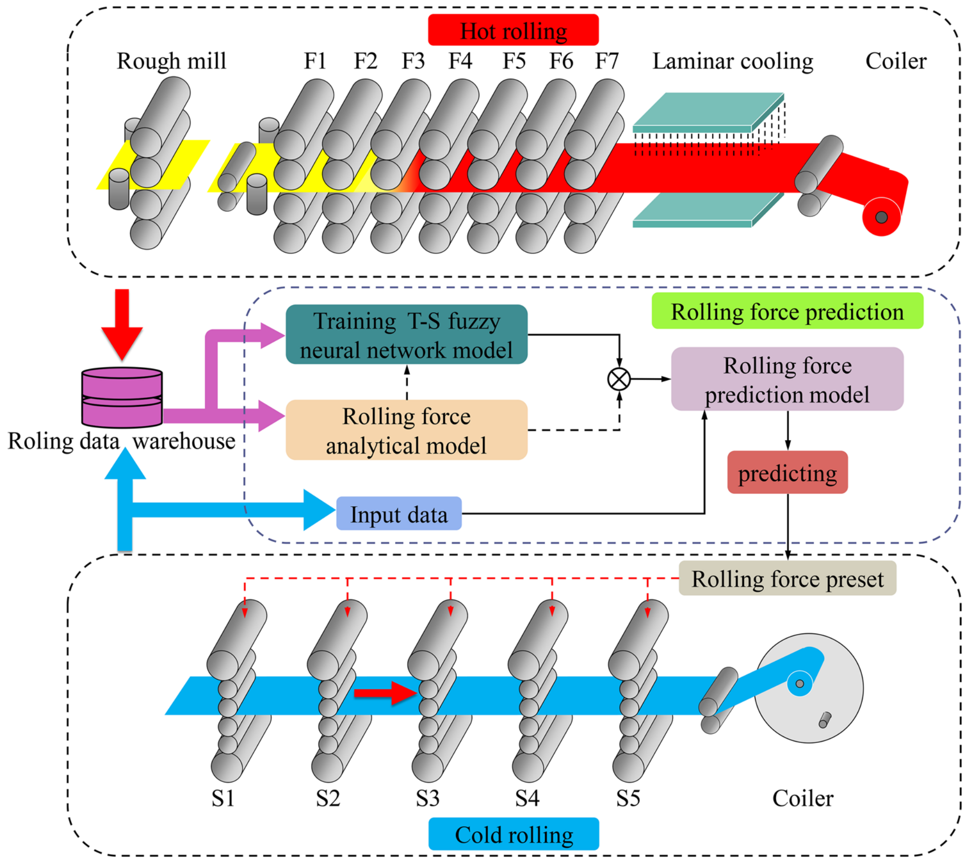

Fig. 1 Combined model for operational structure predicting rolling force

control quantity by fuzzy reasoning, which is not yet directly usable as a controlled quantity and needs to be converted into a precise quantity. The anti-fuzzification module converts the fuzzy output quantity into an actual quantity used for control.

Commonly used fuzzy systems can be classified into Mamdani, Zadeh, and Takagi–Sugeno (T-S) based on different fuzzy inference methods. The T-S fuzzy model can arbitrarily approximate a nonlinear function. The model can be automatically updated so that the affiliation

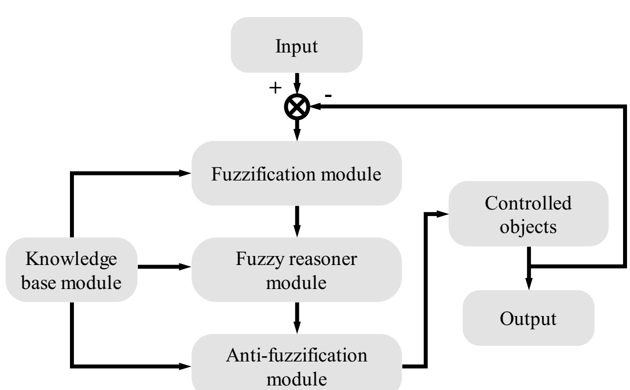

Fig. 2 Components of fuzzy controller

functions of fuzzy subsets are constantly corrected and can model complex nonlinear systems with fewer rules. Hence, the model is a commonly used method for modeling critical nonlinear uncertain fuzzy systems [8].

The T-S fuzzy system can be defined in terms of the mth fuzzy rule by the following form.

$$\text{Rules}^m\text{: If } x_1 \text{ } is \text{ } S_1^m, x_2 \text{ } is \text{ } S_2^m, \cdots, x_n \text{ } is \text{ } S_n^m$$
$$\text{then } y_m = P_0^m + P_1^m x_1 + \cdots + P_n^m x_n$$

where x is a fuzzy linguistic variable, i.e., the input; y represents the output derived from the fuzzy rule; ${S_n}^m$ is the fuzzy subset; and ${P_n}^m$ is the system parameter.

The affiliation function for each input variable relative to the fuzzy subset is calculated as follows [9]:

$$\mu_{S_i^j}(x_i) = \exp\left[-\left(x_i - C_i^j\right)^2 \Big/ W_i^j\right], i = 1, 2, \cdots, n, j = 1, 2, \cdots, m \tag{1}$$

where C_i^j and W_i^j are the affiliation function's center and width, respectively.

The fuzzy calculation of each affiliation degree is performed using the multiplicative rule.

$$\omega_j = \mu_{S_1^j}(x_1)\mu_{S_2^j}^2(x_2)\cdots\mu_{S_n^j}^n(x_n), j = 1, 2, \cdots, m \tag{2}$$

The normalization formula for the output layer is as follows:

$$\overline{\omega}_j=\omega_j \Big/ \sum_{\gamma=1}^{m} \omega_\gamma, j = 1, 2, \cdots, m \tag{3}$$

Finally, the output of the fuzzy model is calculated as follows:

$$y = \sum_{j=0}^{m} \overline{\omega}_j y_j \tag{4}$$

2.2 T-S fuzzy neural network learning

Both fuzzy systems and neural networks aim to solve complex multifactor, nonlinear modeling problems by simulating the human thought process. Neural network models are simple, malleable, and have strong learning capabilities. Nevertheless, they tend to fall into local convergence when dealing with complex nonlinear problems. They do not make good use of existing empirical knowledge to analyze and deal with fuzzy issues, requiring a large sample size for model training. In contrast, T-S fuzzy systems can be controlled intuitively based on human empirical knowledge and need a smaller sample size. Therefore, a proper combination of the T-S fuzzy system and neural network to form a T-S fuzzy neural network can give full play to the advantages of both and form a model system with more powerful performance [10]. The T-S fuzzy neural network model can be regarded as a nonlinear model that can approximate any nonlinear system with arbitrary accuracy and mainly contains antecedent and posterior networks, as shown in Fig. 3.

The antecedent network matches the antecedents of fuzzy rules and consists of four main layers. The first layer is the input that transmits the input vector $X=[x_1, x_2,\ldots,x_n]^T$ to the fuzzification layer; the second layer is the fuzzification layer, where each node represents a linguistic variable value, and Eq. (1) calculates the affiliation function for each input variable relative to the fuzzy subset; and the third layer's role is fuzzy rule calculation, where each node represents a fuzzy rule and by Eq. (2) calculates the degree of applicability of each fuzzy rule. The fourth layer has the same number of nodes as the fuzzy rule calculation layer, which is used to perform the normalization calculation operation via Eq. (3) and is used as

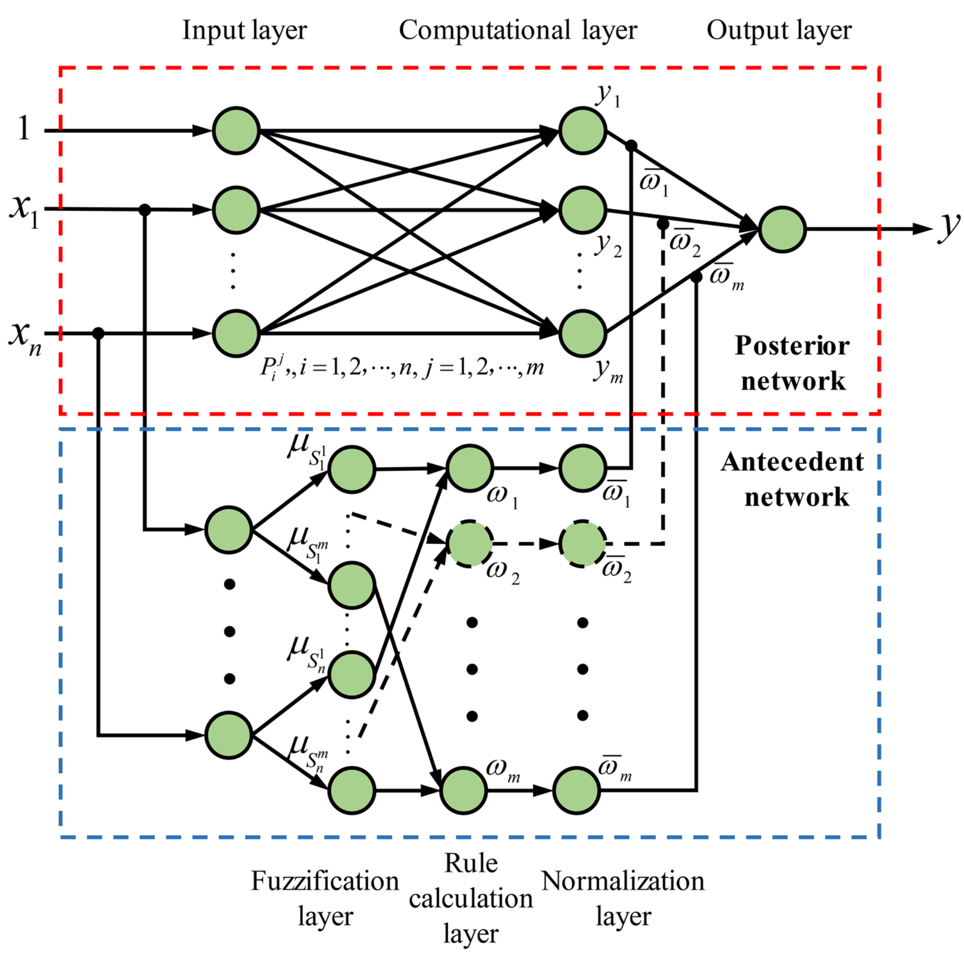

Fig. 3 Structure of T-S fuzzy neural network

the connection weights for the third layer of the posterior network.

The posterior network generates the posterior of the fuzzy rule and consists of m structurally identical small networks, each of which produces an output quantity. The posterior network consists of three layers. The first layer is input, taking the sample data input and transmitting it to the computational layer, where the input value of the 0th node in the first layer is 1. Its role is to provide the constant term in the posterior of the fuzzy rule. The role of the computational layer is to calculate the posterior of each fuzzy rule. The output layer uses Eq. (4) to calculate the output of the fuzzy neural network.

Fuzzy neural networks require self-learning and updating the system's parameters, such as connection weights and the centers and widths of the affiliation functions.

1. The error function was first calculated [11].

$$E = \frac{1}{2}\left(y^{\mathrm{desire}} - y^{\mathrm{predict}}\right)^2 \tag{5}$$

where y^{desire} and y^{predict} are the desired and predicted outputs, respectively.

2. Connection weight correction for T-S fuzzy neural networks.

$$\frac{\partial E}{\partial p_i^j} = \left(y^{\mathrm{desire}} - y^{\mathrm{predict}}\right)\overline{\omega}_j x_i \tag{6}$$

$$p_i^j(k+1) = p_i^j(k) - \tau \frac{\partial E}{\partial p_i^j} \tag{7}$$

where p_i^j, τ, and x_i represent the neural network coefficient, learning rate, and model input, respectively.

3. Affiliation function parameter correction.

$$C_i^j(k+1) = C_i^j(k) - \tau \frac{\partial E}{\partial C_i^j} \tag{8}$$

$$W_i^j(k+1) = W_i^j(k) - \tau \frac{\partial e}{\partial W_i^j} \tag{9}$$

where C_i^j and W_i^j are the center and width of the affiliation function, respectively.

3 Combined rolling force prediction models

3.1 Rolling force analytical model

The rolling force mathematical model determines the quality of the cold-rolled products and parameter preset accuracy. The front slip and rolling moment models are based on the rolling force model, which is also the basis for calculating other mill setting parameters such as roll slits. Figure 4 shows the deformation zone of the cold-rolled strip. The action of the rolling force deforms the metal. The deformation zone of the rolled part, according to the nature of the deformation, can be divided into an elastic deformation zone, plastic deformation zone, and elastic recovery zone. The total rolling force of the rolled part is the sum of the rolling force of the three regions [12, 13]. Due to the complexity of the deformation process, it is not easy to use a mathematical formula to describe the process accurately. Hence, the current analytical model of rolling force is based on the actual situation in the field, ignoring the role of certain factors in the approximate model.

The most widely used rolling force analytical model in the field of continuous cold rolling in recent times is the Hill simplified form of the Bland-Ford model, calculated as follows [14]:

$$P = Bk_p k_T \sqrt{R'(H-h)}Q_p Z_{\mathrm{new}} \tag{10}$$

where H represents the entrance strip thickness, h represents the exit strip thickness, and Z_{new} represents the rolling force adaptive factor.

$$Z_{\mathrm{new}} = Z_{\mathrm{old}} + \lambda(Z^* - Z_{\mathrm{old}}) \tag{11}$$

where Z_{new} is the adaptive coefficient's new value, Z_{old} is the old value of the adaptive coefficient, Z^* is the measured

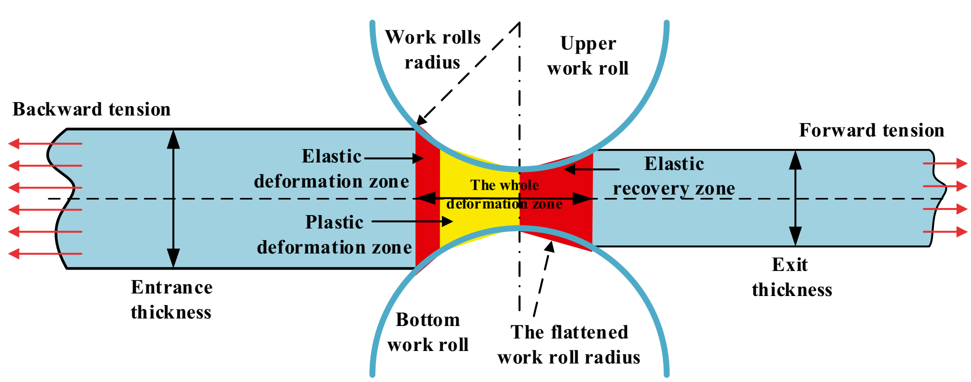

Fig. 4 Schematic diagram of cold-rolled deformation zone

value corresponding to this coefficient using the measured value, and λ is the gain coefficient. The Hitchcock formula is used to calculate the work roll radius after flattening as follows:

$$R' = (1 + \frac{C_H \cdot P}{B(H-h)}) \cdot R \tag{12}$$

where R is the work roll radius, B is the width of the strip, and C_H is a constant, generally taking the value of 0.000214.

$$k_T=(1-\frac{t_b}{k_p}) \cdot [1.05+0.1 \cdot \frac{1-(t_f/k_p)}{1-(t_b/k_p)} - 0.15 \cdot \frac{1-(t_f/k_p)}{1-(t_f/k_p)}] \tag{13}$$

where k_T is the tension factor; t_b and t_f are the forward and backward tensions of the stand, respectively; and the simplest commonly used model for the stress state factor is as follows [15]:

$$Q_p = 1.08 - 1.02 + 1.79 r\mu\sqrt{1-r}\sqrt{(R'/h)} \tag{14}$$

where r is the reduction rate, and μ is the friction coefficient, calculated as follows:

$$\mu=\left(\mu_0+\frac{\mu_1}{v+\mu_2}+\mu_3 \cdot v\right)\left(\frac{\mu_4}{1+N_r \cdot \mu_5}\right) \tag{15}$$

where $\mu_0 \sim \mu_5$ are the friction coefficient parameters, v represents the rolling speed, and N_r is the number of rolls rolled after the roll change. The deformation resistance of the strip is related to the steel grade and increases with the degree of cumulative deformation, which can be calculated as follows [16]:

$$k_p = k_s(1000\beta)^\alpha \tag{16}$$

where β is the strip deformation rate, α is a constant, and k_s is the static deformation resistance.

$$k_s = l(\sum \varepsilon + m)^n \tag{17}$$

where l, m, and n are empirical coefficients, and $\sum \varepsilon$ is the cumulative deformation.

The cold rolling process is multivariable, nonlinear, strongly coupled, time-varying, and complex. The current rolling force analytical model is based on the single cold rolling process and has been heavily simplified and assumed. The initial deformation resistance is determined according to the type of material, without taking into account the genetic influence of the finish rolling temperature and coiling temperature, and without being able to make timely and optimal adjustments to the changes in the incoming material conditions, on-site process conditions, and equipment working conditions. This eventually leads to significant deviations between the rolling force setting results and the actual value. As shown in Fig. 5, the linearity between the actual rolling force of the fifth stand of the cold rolling mill and the set value of the rolling force calculated by the analytical model is extremely poor, with a root mean square R-square of 0.41. This cannot satisfy the needs of high precision production and low cost, resulting in the appearance of edge waves at the head of the cold-rolled strip as shown in Fig. 6. This reduces the quality of the finished cold-rolled sheet and the yield of the finished material.

3.2 Rolling force prediction model

Most of the current rolling force prediction models using artificial intelligence algorithms choose the entrance thickness, exit thickness, forward tension, backward tension, fundamental material deformation resistance values, strip width, and work roll radius for each stand of cold rolling as inputs to the model [17–19]. The friction coefficient is not considered an input node to the model as the emulsion used in the same mill does not change frequently. Hot rolling is a previous process to cold rolling. There is a solid genetic evolutionary relationship between the processes. The finished hot-rolled product is used as the raw material for cold rolling, and the nonlinear effects of the finish rolling temperature and coiling temperature of the hot-rolling process on the tissue properties of the finished hot-rolled strip are inherited into the cold rolling process, which then affects the cold rolling force setting accuracy. However, none of the current rolling force prediction models consider the genetic influence of the hot rolling process parameters, so in this paper, the finish

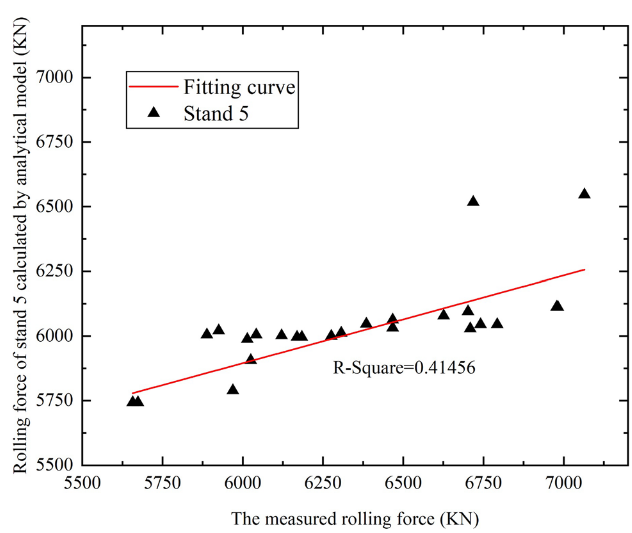

Fig. 5 Measured and set values of rolling force of fifth stand

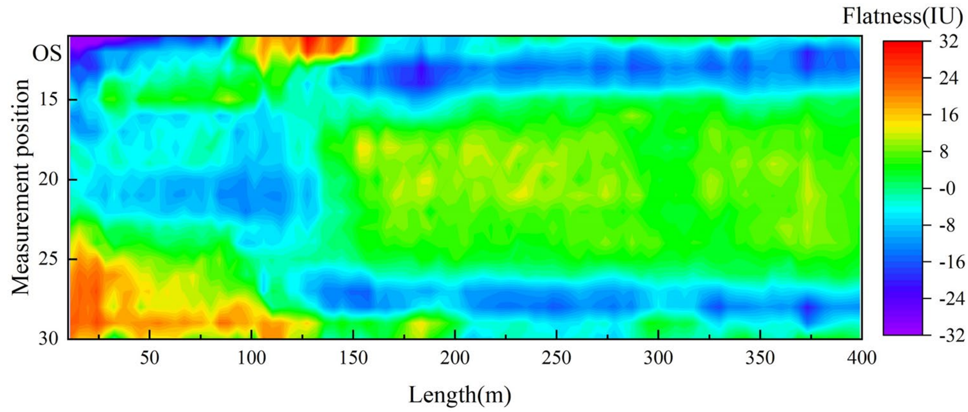

Fig. 6 Schematic diagrams of cold-rolled strip flatness

rolling temperature and coiling temperature are added to the T-S fuzzy neural network model inputs based on the above parameters.

This paper proposes three ways of combining T-S fuzzy neural networks and the rolling force analytical model.

1. First, the rolling force analytical model calculated the primary value. Then the T-S fuzzy neural network predicts the rolling force's deviation coefficient γ, and the two are multiplied together as the rolling force prediction, as shown in Fig. 7. Note that the input for training the T-S fuzzy neural network model is the actual measured values of the selected hot and cold rolling parameters, and the output for training the T-S fuzzy neural network model is the deviation coefficient γ_{train}, calculated as follows:

$$\gamma_{train} = P_{measured} / P_{analytical} \tag{18}$$

where $P_{measured}$ is the rolling force measured value, and $P_{analytical}$ is the calculated value of the rolling force analytical model.

2. The rolling force analytical model calculated the primary value. Next, the T-S fuzzy neural network predicts the rolling force deviation ΔP, and the two are added together as the rolling force prediction, as shown in Fig. 8. The inputs for training the T-S fuzzy neural network model are also the actual measured values of the hot and cold rolling parameters. Nevertheless, the output for training the T-S fuzzy neural network model is the rolling force deviation ΔP_{train}, calculated as follows:

$$\Delta P_{train} = P_{measured} - P_{analytical} \tag{19}$$

where $P_{measured}$ is the rolling force measured value, and $P_{analytical}$ is the calculated value of the rolling force analytical model.

3. The third combination directly uses the calculated value of the rolling force analytical model as an input terminal of the T-S fuzzy neural network without destroying the self-learning process of the analytical model and finally achieve the prediction of the rolling force with the structure shown in Fig. 9.

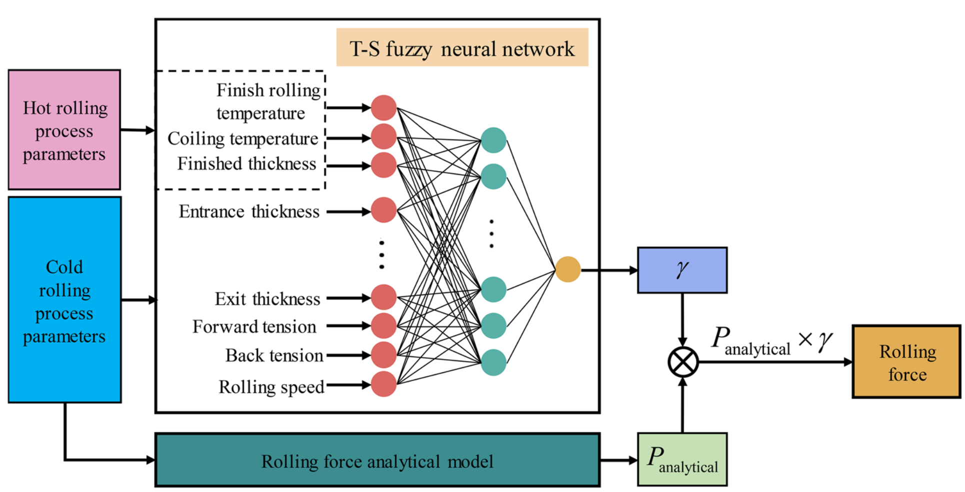

Fig. 7 Schematic diagrams of multiplicative combination structure

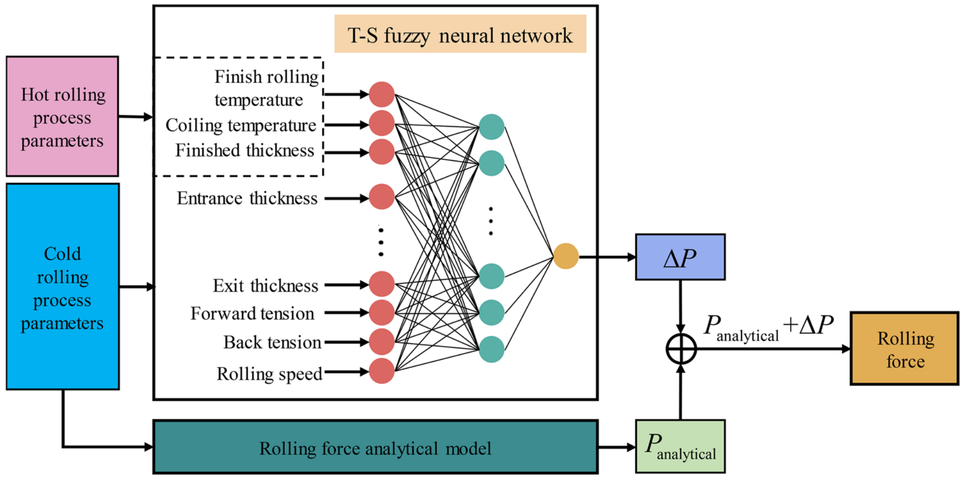

Fig. 8 Schematic diagram of additive combination structure

4 Simulation results and discussion

4.1 Data preprocessing

This paper selects historical production data from a cold rolling industrial site. The corresponding process parameters of hot rolling are obtained as the basis for model training through an internal integrated hot–cold rolling data acquisition and storage platform. The steel selected for this paper is MRT-4. The acquisition and processing of the dataset dramatically affect the performance and prediction accuracy of the model. Some of the sample data measured by sensors during the production process are listed in Table 1. Many outliers and missing values seriously affect the model training and the model's prediction performance and generally have to be processed after reading. The data processing consists of two steps. The first step is to calculate the deviation of each variable in the dataset relative to the mean value of the variable so that the degree of deviation of different variables can be obtained. In this paper, we use the 3σ criterion to detect and eliminate the outliers in the data. The second step is to process each variable with the standard deviation of the variable dataset so that each variable is processed to get within a smaller interval, avoiding certain variables. The order of magnitude is particularly large or small, which interferes with the final results, and the normalization used in this paper is as follows [20, 21]:

$$x_i' = \frac{x_i - \min\{x_j\}}{\max\{x_j\} - \min\{x_j\}}, (1 \le i \le n, 1 \le j \le n) \tag{20}$$

where $\max\{x_j\}$ and $\min\{x_j\}$ are the maximum and minimum data points in the dataset X, respectively, and $x_i{}'$ is the normalized data value.

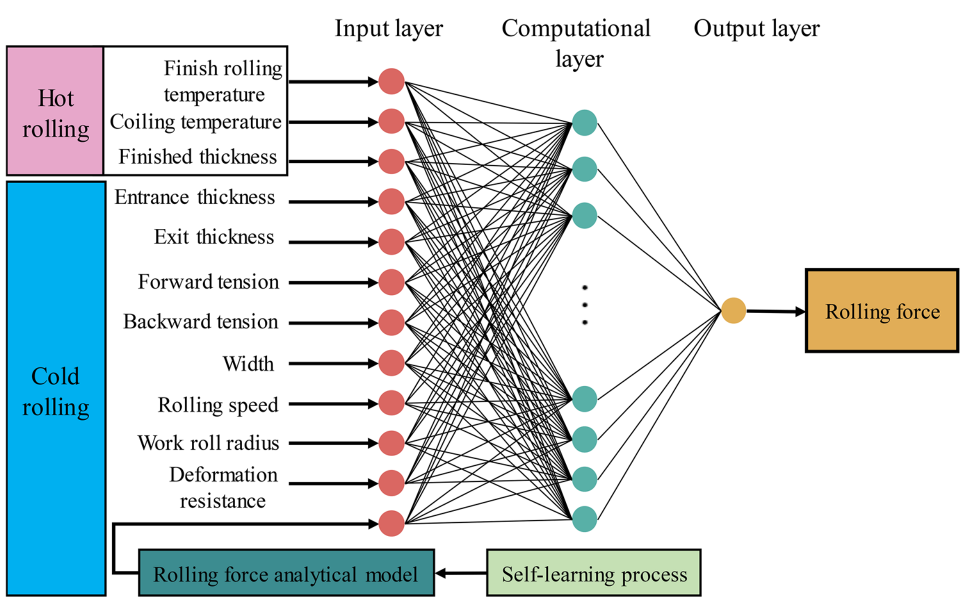

Fig. 9 Structure of third combined prediction model form

Table 1 Part of experimental data

Number	Finish rolling temperature (℃)	Coiling temperature (℃)	Strip width (mm)	S1 entrance thickness (mm)	S5 exit thickness (mm)	S1 rolling force (KN)	S5 rolling force (KN)
1	860	575	873	1.161	0.180	7950	6063
2	861	568	872	1.168	0.181	7931	6000
3	870	573	918	1.196	0.199	8193	6219
4	865	569	897	1.182	0.190	8104	6030
5	878	573	896	1.193	0.200	7973	6002
2897	862	571	957	1.214	0.210	8838	6554
2898	873	570	954	1.221	0.212	8417	6469
2899	875	573	917	1.206	0.211	8115	6118
2900	860	575	896	1.202	0.201	8009	6078

4.2 Evaluation of model accuracy

After removing the outliers from the data, the total remaining data were 2868. To ensure that the model has a strong learning capability, we use most of the data for training the model and the rest for testing the model's accuracy. The number of iterations for the T-S neural network model is 2000. To compare each model's prediction accuracy and generalization ability more thoroughly, three different performance criteria (MAE, MAPE, and RMSE) were selected as the basis for evaluation in this paper.

The mean absolute error (MAE) is calculated as follows:

$$MAE=\frac{1}{n}\sum_{i=1}^{n}\left|y_i-O_i\right| \tag{21}$$

The mean absolute percentage error (MAPE) is shown below.

$$MAPE=\frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i-O_i}{y_i}\right|\times 100\% \tag{22}$$

The root mean square error (RMSE) is calculated as shown below.

$$RMSE=\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i-O_i\right)^2} \tag{23}$$

where y_i and O_i are the desired output and predicted values of the test set, respectively.

Additionally, to verify the advantages of the combined design of the intelligent algorithm model and the analytical model for rolling force prediction, the T-S fuzzy neural network model, which was not considered in combination with the analytical model, was additionally selected to participate in the simulation comparison tests, and named T-S. The input of the separate T-S model was only the hot and cold rolling process parameters. The other three combined models for rolling force prediction are named Combined Model I, Combined Model II, and Combined Model III, as shown in Figs. 7, 8 and 9, respectively. Table 2 lists the results of the three performance evaluations for the T-S model, Combined Model I, Combined Model II, and Combined Model III. All results are averaged over 30 experiments on the test set to avoid the effect of chance errors. The best performance results for each evaluation metric appear in boldface in Table 2.

A comparison of the performance metrics of the four models in Table 2 indicates that all three forms of the combined model outperform the T-S fuzzy neural network model alone in all aspects of performance, which also demonstrates that the combined model is better than the T-S fuzzy neural network model in predicting rolling force for all five stands. Compared to the three combined models, Combined Model III, which directly uses the calculated values from the rolling force analytical model as input to the T-S fuzzy neural

Table 2 Performance of our models

Stand	T-S model			Combined model I			Combined model II			Combined model III		
	MAE	MAPE (%)	RMSE	MAE	MAPE (%)	RMSE	MAE	MAPE (%)	RMSE	MAE	MAPE (%)	RMSE
1	179.19	2.25	221.98	153.15	1.92	193.95	148.36	1.86	189.14	**141.73**	**1.78**	**183.62**
2	161.40	2.28	201.49	152.78	2.16	184.44	138.74	1.97	168.98	**133.58**	**1.90**	**169.53**
3	235.04	3.25	275.26	**207.95**	**2.90**	257.76	227.48	3.15	326.66	212.94	2.94	**254.97**
4	191.46	2.76	229.17	165.18	2.38	201.99	176.26	2.53	218.36	**162.11**	**2.36**	**196.22**
5	170.27	2.74	218.63	135.07	2.21	175.55	137.29	2.24	173.27	**130.31**	**2.14**	**160.17**

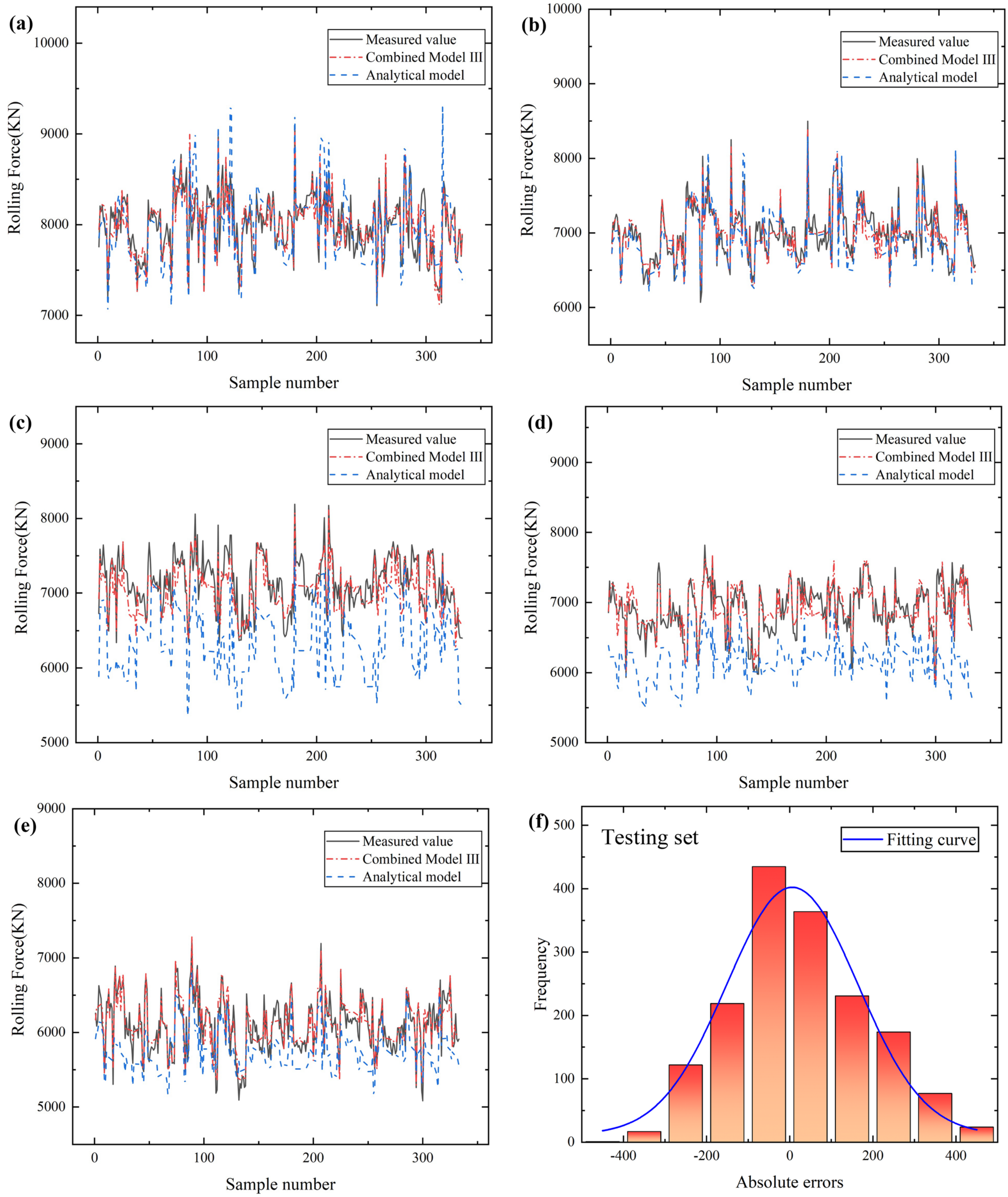

Fig. 10 Comparison of rolling force for all stands **a** Stand 1, **b** Stand 2, **c** Stand 3, **d** Stand 4, **e** Stand 5, and **f** absolute error histogram of predicted rolling force from measured value for all stands

network without disrupting the traditional rolling force self-learning, showed better prediction capability and lowered rolling force prediction errors for the first, second, third, and fifth stands than the other two combined models. While the model performance was evaluated for the third stand, Combined Model I showed a better prediction of rolling force. Nevertheless, the prediction errors of the Combined Models I and III were similar and better than Combined Model II with the prediction errors of rolling force in the third stand. This paper concludes that Combined Model III has the best performance and better prediction accuracy among the five cold-rolled stands.

4.3 Analysis of simulation results

As seen in Fig. 10a–e, the results of the five rolling forces predicted using the combined model III are all close to the actual rolling force. Although the first and second stands of the rolling force analytical model have relatively small errors with the measured rolling force, from the third stand to the end of the fourth stand, there is a significant deviation between the rolling force analytical model and the measured rolling force. The fifth stand is slightly better, but there is still a significant error between the two. As the fifth stand is the last stand of cold rolling, the accuracy of the rolling force setting is substantial for the accuracy of the strip exit shape and thickness, and the existing analytical model of rolling force is unable to meet the requirements of high precision rolling production. Combined Model III is designed to combine the advantages of both models for data prediction with better usability and superiority. Figure 10f shows a histogram of the absolute error between the predicted rolling forces of all stands using Combined Model III and the measured rolling forces of all stands, and the absolute errors trend toward a normal distribution centered on 0.

5 Conclusion

Based on the analysis of rolling principles, this paper made full use of collected hot and cold rolling site data to establish a rolling force prediction model based on a data-driven and mechanistic fusion approach, and analyzed the performance of the model predictions to provide a reference for the online prediction of cold rolling force, as follows.

1. Analyzing the existing cold rolling force modeling methods, both the mechanism-based analytical model and the data-driven intelligent algorithm model relied on the single scold rolling process, ignoring the genetic influence of the hot rolling process parameters on the cold rolling process. With the current development of the industrial Internet, data penetration between hot and cold rolling has been achieved, making it feasible to predict rolling force based on both hot and cold rolling data.
2. The T-S fuzzy neural network model, which is a combination of the T-S fuzzy system and neural network, combines the advantages of the fuzzy system and neural network and makes up for the disadvantages of both, giving it an excellent inference capability, powerful self-learning, self-adaptivity, and associative memory capability, which are highly advantageous in dealing with nonlinear systems and fuzzy information. Therefore, this paper chose the T-S fuzzy neural network as the data-driven support for the rolling force modeling process.
3. To fully utilize the characteristics and advantages of various models, this paper constructed three different forms of combined models for rolling force prediction by combining analytical models and data-driven T-S fuzzy neural network models. Supported by a large amount of field data, from which the knowledge of data statistics is used, the laws required for the models were summarized, and error corrections were made to the purely theoretical models to improve the prediction accuracy of the rolling force models.
4. The rolling force combined prediction model has more robust data prediction and learning capabilities than the intelligent algorithm model or the analytical model alone through experimental comparison. In particular, the accuracy and reliability of the combined model are better than other models in that the calculated values of the analytical model are directly used as input to the T-S fuzzy neural network, so this form of the combined model can provide an essential reference for online prediction of cold rolling force and high precision rolling production and is suitable for online application in multiroll cold rolling mills.

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Declarations

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